

An Introduction to Loki-Infect

An Agent-Based Model for Engineering Strategies to Mitigate the Impact of Influenza Epidemics

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Outline

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- Seasonal Influenza
- Pandemic Influenza
- Modern Warfare

2 Core Model

- Fundamentals
- Adding More Realism
- Generating Social Networks

3 Studies

- Healthcare Environments
- Cost Benefit Analysis
- A Biophysical Model



Seasonal Influenza

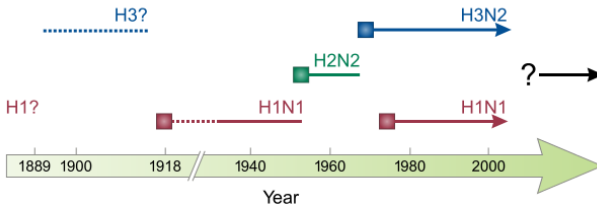
- Molinari et al. (2007) found that, in the United States alone, seasonal influenza is responsible for:
 - 610,660 (undiscounted) life years lost,
 - 3.1 million hospitalized days and 31.4 million outpatient visits,
 - annual direct medical costs averaging \$10.4 billion, and
 - a total economic burden of \$87.1 billion.



Pandemic Influenza

- Periodically, a novel strain of influenza is transmitted to humans from other animals (typically pigs and birds), causing a **pandemic**.

Influenza A virus subtypes in the human population



Major Pandemics of the 20th Century

1918 Spanish Flu (H1N1)

- Case fatality rate between 10% and 20%.
- Between 20 million and 100 million killed.

1957 Asian Flu (H2N2)

- Case fatality rate: 0.13%.
- 1.0 to 1.5 million deaths.

1968 Hong Kong Flu (H3N2)

- Case fatality rate: $< 0.1\%$.
- 0.75 to 1.0 million deaths.

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Recent scares

2003 Avian Flu (H5N1)

- 510 cases in humans, resulting in 303 deaths.
- Little evidence of human-to-human transmission.

2009 Swine Flu (H1N1)

- Total worldwide deaths: 14,286.
- Many similarities to 1918, including disproportionately high incidence of infection and fatality among young people.
- First global pandemic since 1968.

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Modern Warfare

- Neuraminidase inhibitors (antivirals)
 - Effective at treating and preventing infection by susceptible strains.
 - However, because of the high mutation rate of influenza, resistant strains are quick to emerge.
- Vaccine
 - Highly effective at preventing infection.
 - Cannot (yet) be produced before a novel strain emerges.
- Personal protective equipment (facemasks, etc.)
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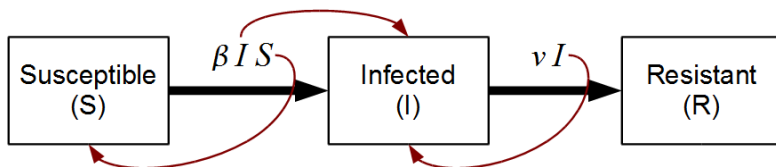
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SIR Models

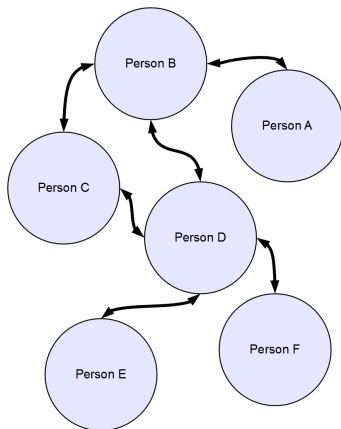


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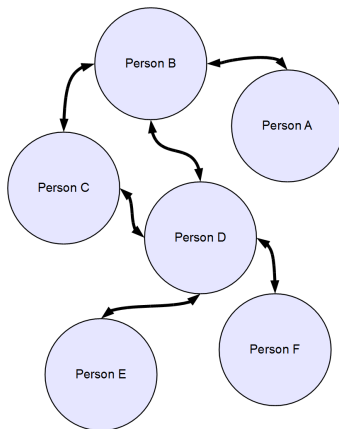
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A Networked Agent-Based Approach



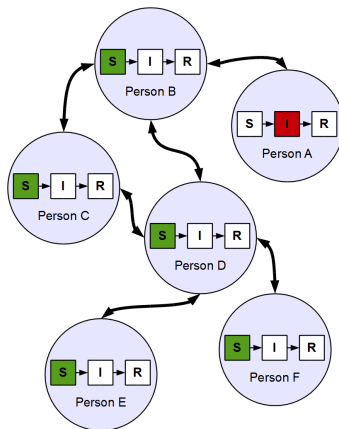
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- In this case, vertices represent people, and edges represent frequencies of interaction.

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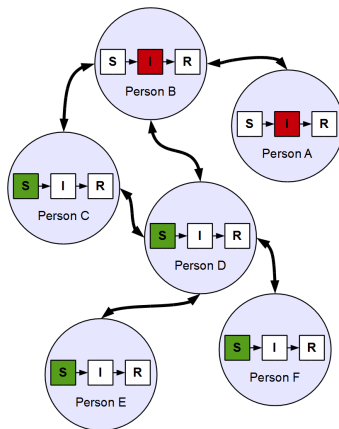
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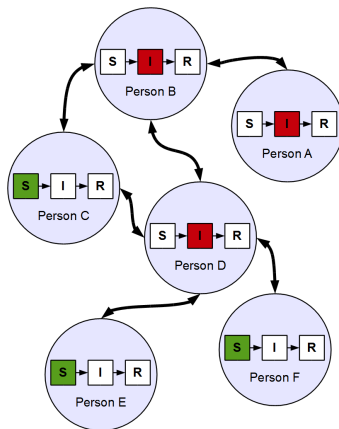
- Rather than lump the population into stocks, we let each agent track its own state.
- When an agent becomes infected, it infects its neighbors with a probability proportional to their interaction frequency.
- After a certain duration in the infected state, an agent transitions to the resistant state.

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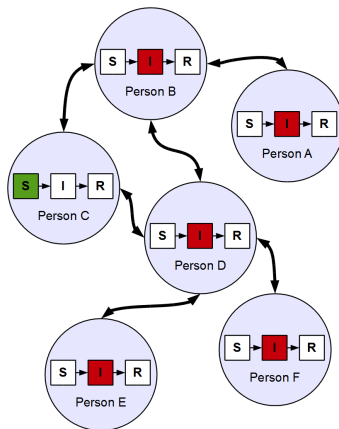
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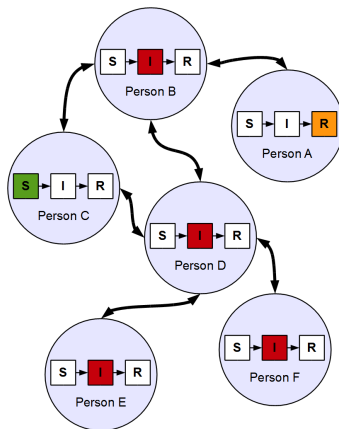
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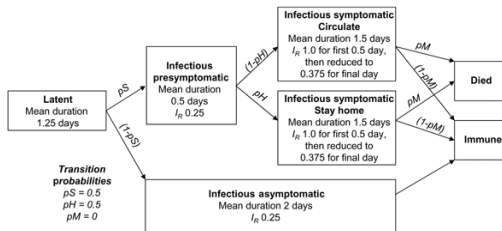
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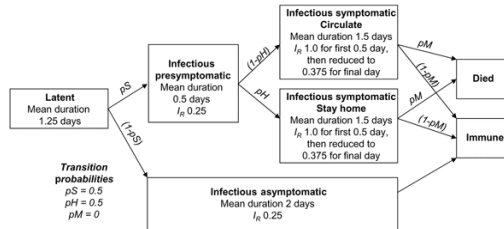
A More Realistic Disease Progression

- While the SIR state machine is simple, it unfortunately allows us too few parameters to adequately characterize a strain of influenza.
- In addition to adding more states, we also make the specific path of disease progression stochastic and couple an agent's infectivity with its state.



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Transmission Dynamics

- Whenever an agent advances to a new infectious state, it attempts transmission to each of its neighbors.
- First, its stay d in the state is randomly selected from an exponential distribution about the mean stay for the state.
- For each incident edge, the agent computes the transmission frequency f_I as

$$f_I = \overbrace{f_C}^{\text{frequency}} \cdot \underbrace{I_R \cdot I_A}_{\text{infectivity}} \cdot \overbrace{S_P \cdot S_A}^{\text{susceptibility}}. \quad (1)$$

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Adaptation and intervention

- Some infected agents will stay at home and self-isolate, reducing their contact frequency with neighboring agents.
- Others will stay home from work to take care of a sick child.
- When an epidemic is detected (after a certain number of diagnoses occur in a given week), a number of interventions can be activated, such as
 - Antiviral treatment, which temporarily reduces infectivity and susceptibility.
 - School closures, in which contact frequency along all school edges is decreased by a compliance factor.
 - Social distancing, in which workplace and friend contacts are decreased by a compliance factor.



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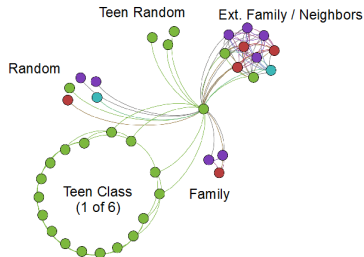
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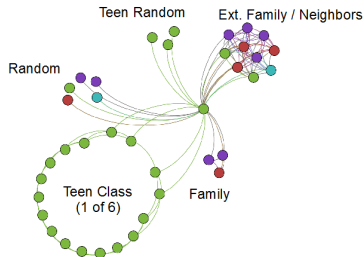
Generating Social Networks

- Rather than use an ideal generator, we instead use a layered approach to construct networks.
- As shown right, each node is the member of multiple sub-networks, such as a family or a classroom.



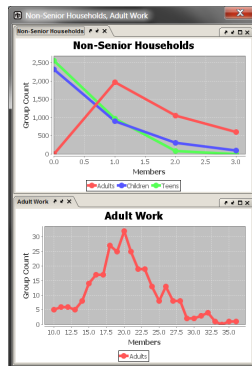
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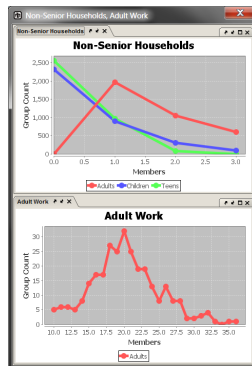
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- Using data from the Census, surveys, and other sources, we can define the distribution of members among groups.
- The best approximation to the user-specified distribution satisfying all other constraints is found.
- Finally, an idealized network is overlaid atop each group.



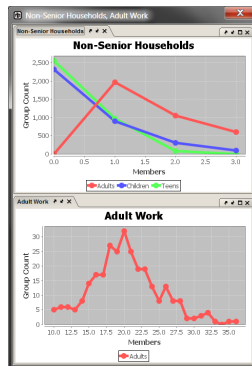
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- Healthcare sites are placed under tremendous strain during an influenza outbreak.
- Healthcare workers and susceptible patients are at a high risk of becoming infected in the healthcare environment.
- Goal: To understand the role of healthcare environments and minimize the impact of an influenza epidemic on healthcare availability.

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Healthcare Environments

- We introduced dynamic healthcare sites into our simulated community in which patients mix with each other and with healthcare workers by creating temporary “on-the-fly” networks.
- When an agent becomes symptomatic, it will, with a certain probability, go to a healthcare site and be accompanied by an adult escort from its family.
- Non-infected agents will periodically visit healthcare sites for routine treatment.
- Each healthcare site has multiple shifts of healthcare workers who interact with each other, with patients, and with their escorts.



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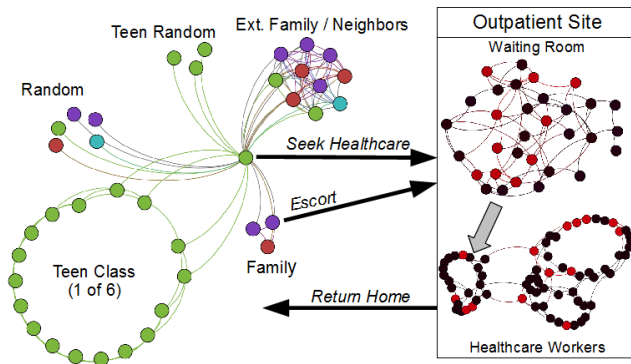


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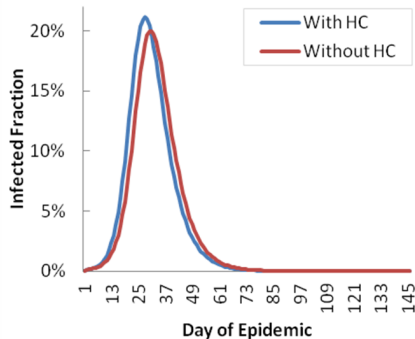


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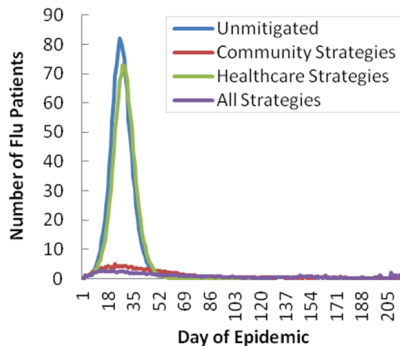
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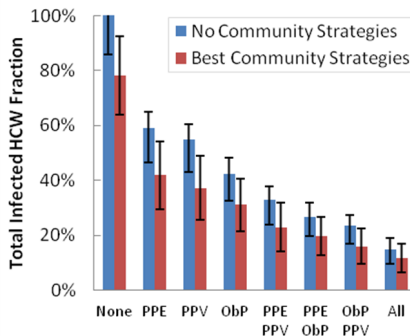
Effect of Healthcare Sites on Epidemic



Mitigating the Load on Healthcare Sites



Ranking of Healthcare Worker Interventions



Cost Benefit Analysis

- We collaborated with Daniella Perlroth, a health economist at Stanford, to combine our influenza model with an economic model to measure the costs and benefits of interventions.
- Considered the costs of healthcare and lost productivity resulting from a given scenario.
- Quality Adjusted Life Years (QALYs)
 - QALYs are a metric of benefit that combines both duration and quality of life.
 - The average quality of life at each time point is ranked from 0 (death) to 1 (perfect health). By integrating over all time points and subtracting from a baseline (no intervention) we get a measure of incremental QALYs gained.



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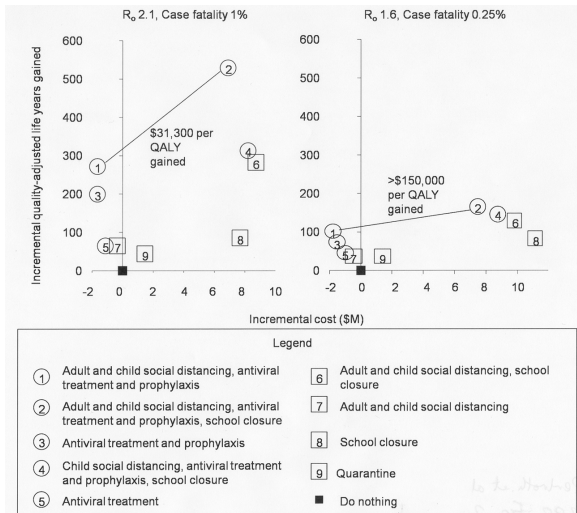


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A Biophysical Model

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- The parameters governing a particular strain of influenza can be distilled down to p , the viral production rate, and b , the cellular infection rate.
- Additionally, each agent has an immune response rate r that we assign to members of the population from user-specified distributions.



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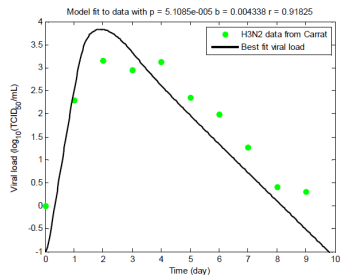
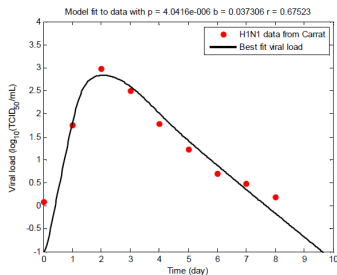
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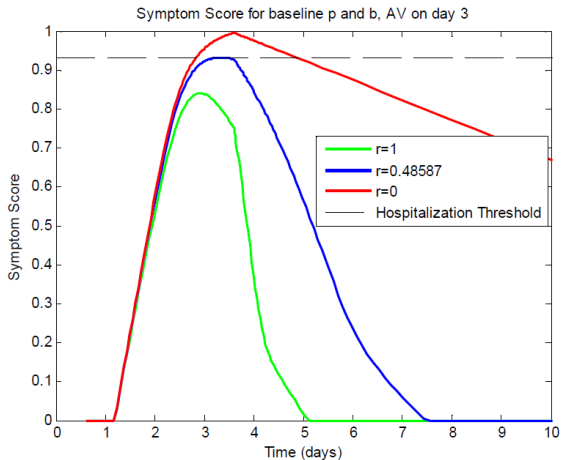
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Sandia
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